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AMENDMENTS TO THE SPECIFICATION

Please replace paragraph [0047] with the following amended paragraph:

[0047] The exponential function offers good opportunities to make a prediction of actual separation losses (T/h) based on an online measurement of feedrate u(t) (T/h), wherein (T/h) is representative of tons per hour. The feedrate may be measured at the inlet of the harvester, e.g. by monitoring the volume of crop material entering the straw elevator, or by measuring the force or torque needed to convey the crop mass into the machine.

Please replace paragraph [0048] with the following amended paragraph:

[0048] Advantageously, the exponential function may take the form of:

$$\hat{y}(t,\vartheta)=\exp(\vartheta u(t))-1 . \tag{1}$$

Equation (1) illustrates that no separation losses occurs for a zero feedrate and the feedrate-loss relation is fully determined by parameter ϑ. The time delay between the feedrate signal *u(t)* and *y(t)* is assumed to be fixed and an optimal fixed time shift (typically 11s) is installed as a compensation. For online measurements, separation losses and feedrate will be expressed in respectively impacts per second (#/s) and Volt (V). To optimize the parameter ϑ, following quadratic criterion $V(\vartheta)$ is proposed in function of prediction error $\varepsilon(t,\vartheta)$ (#/s):

$$V(\vartheta)=E\{0.5\varepsilon^2(t,\vartheta)\} \qquad \varepsilon(t,\vartheta)=y(t)-\hat{y}(t,\vartheta). \tag{2}$$

Wherein, V is a the quadratic error criterion, selected by the Applicants as a value for the precision of ϑ.

$E\{.\}$ is the expected value function. After an estimation or a calculation of ϑ, the actual variables $y(t)$ are compared to the calculated variables $\hat{y}(t,\vartheta)$ and the difference ε is squared over the measurement range of t.

So, for continuous functions over the interval (t_0,t_e), $E\{.\}$ may be set equal to:

$$V(\vartheta)=\frac{1}{t_e-t_o}\int_{t=t_0}^{t_e}0.5\varepsilon^2(t,\vartheta)dt$$

For discontinuous functions involving N discrete points, $E\{.\}$ may be set equal to

$$V(\vartheta)=\frac{1}{N}\sum_{k=1}^{N}0.5\varepsilon^2(k,\vartheta)$$

Please replace paragraph [0054] with the following amended paragraph:

[0054] When applied to the present optimization problem, the quasi-Newton optimization scheme can be transformed into following gradient scheme, which could be called a "stochastic Newton algorithm":

$$V(\vartheta)=EH(\vartheta,e(t)) \tag{6}$$

$$\hat{\vartheta}(t)=\hat{\vartheta}(t-1)+\gamma(t)\left[\overline{V}''\left(\hat{\vartheta}(t-1),e^t\right)\right]^{-1}Q\left(\hat{\vartheta}(t-1),e^t\right) \tag{7}$$

where $\overline{V}''(.)$ denotes the approximate Hessian, $-Q(.)$ is the gradient of $H(x,e)$ with respect to x and e^t indicates that the approximation depends on previous noise values $e^t = e(t), e(t-1), \ldots$ When this scheme is applied to the problem definition of equation (1) and (2), following algorithm is obtained for the model parameter $\vartheta(t)$:

$$\hat{\vartheta}(t) = \hat{\vartheta}(t-1) + \gamma(t) r^{-1}(t) \psi\left(t, \hat{\vartheta}(t-1)\right) \varepsilon\left(t, \hat{\vartheta}(t-1)\right) \tag{8}$$

where $\psi(t,\vartheta) = \dfrac{d\hat{y}(t,\vartheta)}{d\vartheta}$ and scalar $r(t)$ corresponds with the instantaneous estimation of Hessian $V''(\vartheta)$. When an exponential process model according to function (1) has been chosen, $\psi(t,\vartheta)$ will be equal to $\exp(\vartheta.u(t)).u(t)$.

$\hat{\vartheta}(t-1)$ is the estimated/optimised value for ϑ, as based on the data available at the time $(t-1)$. A new estimate/optimisation $\hat{\vartheta}(t)$ for ϑ can be made at the next time t and its value will be calculated from a function involving the previously estimated available value $\hat{\vartheta}(t-1)$ and the error $\varepsilon(t)$ between the actual values y available (including the new one at time t) and the calculated values for the same interval, using the previous estimate $\hat{\vartheta}(t-1)$.

$$\varepsilon\left(t, \hat{\vartheta}(t-1)\right) = y(t) - \hat{y}\left(t, \hat{\vartheta}(t-1)\right)$$